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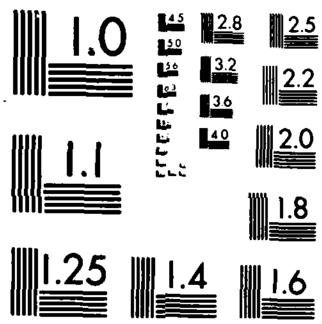

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ASPIRATION LEVEL AND THE REVERSAL OF THE PREFERENCE REVERSAL PHENOMENON

JEFF T. CASEY

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The preference reversal phenomenon (PRP) challenges the validity of nearly all descriptive decision theories. Subjects exhibiting PRP choose a P bet (with a large chance of a small gain) over a $ bet (small chance of large gain). But when asked to put buying or selling price bids on the two bets, they bid more for the $ bet. This pattern is termed P choice reversal. The opposite pattern, $ choice reversal, is rare.

A satisficing hypothesis is developed which says that, when bids are

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Aspiration Level and Reversal of the Preference Reversal Phenomenon

The preference reversal phenomenon is a violation of the canons of rational choice that has perplexed numerous investigators. It is probably the best-documented member of a growing family of anomalies called *framing effects*. Framing effects are demonstrations that the same decision problem, when posed in different ways, reliably elicits different preferences from the decision maker (Tversky and Kahneman, 1981; Slovic and Lichtenstein, 1983). Under the assumption that the alternative problem representations are formally identical, these changes in preference create serious doubts concerning (1) human rationality in judgment and decision making, (2) the potential of existing formal analytic techniques for circumventing human limitations, and (3) the validity of nearly all descriptive theories of decision making.

In preference reversal experiments, a decision problem involving two probabilistic alternatives is posed in two different ways. One "framing" requires a binary choice, while the other requires two separate numerical judgments. Consider the choice between a "long-shot" gamble, called a $ bet, which gives a modest chance of winning a relatively large sum of money, and a "safe" gamble, called a P bet, which gives a good probability of winning a relatively small sum. If the two bets have similar expected values and are offered at no cost to the player, many people choose the P bet over the $ bet. However, when asked for each bet separately "What is the least money for which you would sell this bet?" most of these people state a higher price for the $ bet than for the P bet. Thus their choices indicate that they prefer the P bet, but their bids to sell the bets indicate that the $ bet is more valuable to them. If it is assumed that the bet receiving the higher bid is the preferred bet, then preference reversal has occurred between the choice and selling price situations. This phenomenon has been replicated in every context in which it has been examined (see Slovic and Lichtenstein, 1983, for a review). It is not attributable to simple explanations, such as indifference or strategic overpricing.

Lichtenstein and Slovic (1971) provided the first report of preference reversal. As an example, one of their experimental problems asked subjects whether they would rather play a $ bet which gave a .2 probability of winning $9 and a .8 probability of losing $.50, or a P bet which gave a .8 probability of winning $2 and a .2 probability of losing $1. Most subjects who chose the P bet subsequently commited a preference reversal by setting a higher selling price for the $ bet than for the P bet. Lichtenstein and Slovic called reversals of this type "predicted" reversals. However, the term *P choice reversal* will be used here. In contrast, very few of the subjects who chose the $ bet subsequently bid more for the P bet than for the $ bet. When reversals of this type did occur, Lichtenstein and Slovic referred to them as "unpredicted" reversals. The term *$ choice reversal* will be used here.

Difficulties Created by Preference Reversal

Concerning (1) above, if P choice reversals occur often in everyday life and if they occur even when the stakes are high, then the phenomenon may represent a serious cognitive deficiency. If preference order over risky alternatives changes reliably as a function of how preferences are

elicited, then there is great potential for external forces to manipulate individuals' preferences. For example, a person exhibiting preference reversal reliably can be exploited via arbitrage (Berg, Dickhaut and O'Brien, 1985; Lichtenstein and Slovic, 1971).

The assumption of rationality on the part of decision makers can be maintained in the face of phenomena such as preference reversal by invoking cost/benefit principles (Payne, 1982). According to a cost/benefit explanation, preference reversal can occur whenever the information processing costs associated with generating "unbiased" responses outweigh the detrimental effects of reversal on decision quality. This sort of second-order explanation is ill-founded, however, unless it can be shown empirically that preference reversal does not occur when the penalties for reversal (or benefits of consistency) are sufficiently high.

Concerning (2), evidence of shortcomings in human judgment and decision making ability have been cited traditionally in support of the contention that, when facing important decisions, people can be helped by formal analytic techniques. However, one of the most popular of such techniques, expected utility decision analysis, is undermined to the extent that preference reversal effects influence the utility elicitation procedure. A common method of obtaining certainty equivalence judgments that can be used to define an individual's utility function for money is to ask for bids to buy or sell hypothetical bets. If the individual is subject to preference reversal, then the utility function is invalid unless it is assumed that choice tasks introduce bias but bidding tasks do not. This assumption would not be allowed in von Neumann and Morgenstern's (1947) expected utility system, because their derivation was based solely on the choice response mode.

Concerning (3), the preference reversal phenomenon violates the invariance criterion of rational choice discussed by Kahneman and Tversky (1984). This principle is required by nearly all axiomatic theories of decision making, including preference theory and expected utility theory (and its popular variants). Because it addresses only the choice response mode, Kahneman and Tversky's (1979) prospect theory fails to deal with the abysmal difficulties created by preference reversal. Thus far, the only attempts to account for preference reversal within the context of a general, axiomatic theory have been made by Bell (1982) and Loomes and Sugden (1982, 1983). If preference reversal occurs frequently in important decisions outside the laboratory, then descriptive theories of decision making must be broadened to include response mode (i.e., choice versus bid) as a major factor. The existing literature points overwhelmingly to the need for such revision (see Slovic and Lichtenstein, 1983).

Overview of the Paper

The purpose of this paper is to explore the predictions of a theoretical approach which, unlike the class of expectation-based decriptive theories mentioned above, is rooted more in psychology than in economics. The organization of this paper is as follows. Methods for eliciting and evaluating preference reversal data are reviewed. The generally accepted explanation of the phenomenon is discussed, along with a brief review of the literature. An alternative hypothesis, based on the concepts of aspiration level and satisficing is developed. This new hypothesis is shown to predict that, under certain conditions, the standard preference reversal pattern

should not only be less frequent, its sign should be reversed. The data of Experiment 1 are shown to support this prediction. It is argued that this new reversal pattern is coherent and sensible. In Experiment 2, Part 1 the task modification which catalyzed the new reversal pattern is identified precisely. The cognitive processes underlying the new reversal pattern are analyzed theoretically and a critical operation identified. In Experiment 2, Part 2 it is shown that, when the standard preference reversal pattern does occur, helping subjects over this critical "hump" causes a dramatic shift to the new reversal pattern. Taken together, these results are shown to cast the preference reversal phenomenon in an entirely new light which stresses the role of motivation in activating top-down, goal-directed satisficing processes and de-emphasizes human information processing limitations.

Eliciting Bids and Evaluting Reversals

In the typical preference reversal experiment subjects are asked to make a number of binary choices between P bets and $ bets. There are, however, two major ways of eliciting bids that can be used to infer which bet is preferred. In the example above, subjects were to suppose that they owned the opportunity to play the bet. They were then to state their minimum selling price for each bet. An alternative is to employ maximum buying price instructions. Under maximum buying price instructions, subjects are to state the largest amount of money they would be willing to pay for the chance to play the bet. (Technically, these prices are usually defined as limiting values such that the individual is indifferent between transacting and not transacting.)

The P choice reversal rate for a pair of bets is the proportion of subjects who bid more for the "long-shot" $ bet than for the "safe" P bet, given that they selected the P bet in the choice task. The P choice reversal rate is unlikely to be zero in an experimental task, since some reversals are bound to occur as a result of simple carelessness or indifference. Perfect consistency is not a realistic standard by which to evaluate the P choice reversal rate. Therefore, the $ choice reversal rate for a bet pair is typically used as the baseline rate of reversal. The $ choice reversal rate is the proportion of subjects who bid more for the P bet than for the $ bet, given that they selected the $ bet in the choice task.

Substantial P choice reversal rates have been found for both selling and buying elicitation methods. However, minimum selling price tasks typically produce a higher rate of P choice reversal than do maxmimum buying price tasks. Lichtenstein and Slovic (1971) reported that, under minimum selling price instructions, 73 percent of subjects made a P choice reversal every time they chose the P bet. Under maximum buying price instructions only 11 percent of subjects always made a P choice reversal.

The Anchoring and Adjustment Hypothesis

The currently accepted explanation of preference reversal was proposed by Lichtenstein and Slovic (1971). The central idea is that people attend more to the probabilities of winning in the choice task, while in the bidding task, they attend more to the amount to win. Attention to probabilities in the choice task produces a propensity to select the P bet.

Since the $ bet offers a relatively large prize, attention to the amount to win in the bidding task causes a relatively high price to be set for the $ bet. The P bet cannot be grossly overpriced, because the amount to win sets an upper limit which is only slightly greater than the expected value.

Lichtenstein and Slovic hypothesized anchoring and adjustment as the mechanism by which bids are generated. Consistent with the attentional explanation, the amount to win is used as a starting point, or anchor, in bidding. The bid is then adjusted downward to take into account the probability of winning. Since such adjustment processes are typically insufficient (i.e., they accomplish only a portion of the needed adjustment), the resulting price is closely related to the amount to win and only partially reflects the small probability of winning. Thus, insufficient adjustment causes $ bets to be overpriced relative to P bets, regardless of which bet is preferred in the choice task.

Recently, the preference reversal phenomenon has been discussed in the context of a much broader concept of "compatibility effects" (Slovic and Lichtenstein, 1983; Tversky and Slovic, 1984). A compatibility effect is "a tendency to weight more heavily those aspects of the stimulus that are most easily mapped into the response" (Tversky and Slovic, 1984). Bids and outcomes are expressed in monetary units, but probability information is not. Therefore, under the assumption that the amount to win from a bet is more salient than the amount to lose (which is near $0), then, in bidding tasks, the amount to win should receive greater weight than the probability of winning. In the choice task there is no obvious stimulus-response compatibility. Thus monetary information should receive less weight in the choice task than in the bidding task.

An explanation of preference reversal might emphasize anchoring and insufficient adjustment or compatibility effects or the combination. In any case, the essential idea is that the amount to win in the $ bet exerts great influence on $ bet bids, but it exerts relatively less influence in the choice task. This general explanation will be referred to as the anchoring and adjustment hypothesis.

Attempts to Demonstrate Preference Consistency

During the years since Lichtenstein and Slovic's (1971) original demonstration, experimental work has concentrated on finding tasks in which preference reversal does not occur. Although the various task designs have modulated the effect over a substantial range, all published experiments have shown significant preference reversal effects. Also, none of the studies have rejected the anchoring and adjustment hypothesis. All of the studies to be discussed in this section used two-outcome bets and minimum selling price instructions. Studies using maximum buying price instructions will be discussed in a later section.

Lichtenstein and Slovic (1973) replicated the preference reversal phenomenon in a Las Vegas casino, using gamblers playing for real money. Outcome feedback was provided immediately after each choice or bidding trial. The P choice reversal rate was .81 and the $ choice reversal rate was .10. In another condition, the signs of each bet's outcomes were changed and the phenomenon was replicated in the loss domain. In this case, it appeared that subjects anchored their bids on the minimum outcome, instead of the maximum outcome.

Lindman (1971) found no effect of several contextual factors on bids. Outcome feedback following each trial resulted in a slight tendency for $ bet bids to decrease relative to P bet bids over trials. However, in many cases, this decrease was not sufficient to bring preference orders for the bidding task into agreement with those for the choice task.

Grether and Plott (1979) identified 13 possible artifacts and/or shortcomings of previous preference reversal experiments and developed procedures intended to overcome these potential problems. These problems included misspecified incentives, information processing costs, income effects, indifference in the choice task, strategic responding in the bidding task, and confusion and misunderstanding on the part of subjects.

Misspecified incentives and information processing costs relate to the issue of whether subjects are sufficiently motivated and whether this motivation is directed toward the goals intended by the experimenter. Income effects could produce changes in risk attitude over trials if subjects atte[illegible] to cumulate their winnings across bet pairs. If subjects were indiffer[illegible] n the choice task, it would be unreasonable to expect them to produce consistent bids and choices. In order to allow for this possibility, subjects were given the option of indicating indifference in the choice task. Indifference responses were excluded from the analysis. The most troublesome sort of strategic responding would be a tendency to state an asking price which is inflated relative to the individual's actual "bottom dollar" price. Lindman (1971) and Lichtenstein and Slovic (1973) addressed this possibility by drawing counteroffer bids at random from a uniform distribution. Subjects were not allowed to change their bids after the counteroffer had been made. Each bet was played or sold, depending on the relationship between the bid and the counteroffer. This method effectively penalized subjects for inflating (or deflating) their bids. Grether and Plott also used a counteroffer procedure for some bets.

To their surprise, Grether and Plott found large preference reversal effects for all experimental conditions. Monetary incentives did not decrease the effect. Also, subjects rarely indicated indifference in the choice task.

Pommerehne, Schneider and Zweifel (1982) argued that Grether and Plott's subjects were insufficiently motivated because of the small monetary amounts of the bets. Nearly all preference reversal experiments have used bets with expected values in the range of roughly $1.50 to $4. Pommerehne et al. used bets with expected values in the range of roughly $139 to $386. Monetary incentives were also employed. The resulting P choice reversal rate (.48) was significantly greater than the $ choice reversal rate (.13). The P choice reversal rate was significantly lower than that found by Grether and Plott. However, Pommerehne et al. did not run a control condition with smaller expected values. Therefore, it is not possible to conclude that the reduction in the P choice reversal rate was due to the increased expected values of the bets (Grether and Plott, 1982).

Reilly (1982) criticized the Grether and Plott study on several counts and attempted to improve upon their method. Reilly attempted to make the instructions more clear and the monetary incentive system more effective. These changes decreased the P choice reversal rate slightly, but it remained quite high. Providing subjects with expected value information also caused a small reduction in the P choice reversal rate. A more interesting finding

was that increasing the amount to lose for some of the bets (e.g., from -$1.00 to -$2.00) resulted in a substantial decrease in the P choice reversal rate. This result suggests that, when the bets offer the possibility of substantial losses, the influence of the $ bet's amount to win in the bidding task is decreased relative to its influence in the choice task.

Mowen and Gentry (1980) replicated the preference reversal phenomenon in a simulated managerial decision task using junior and senior business students as subjects. The bets had outcomes ranging from a loss of $150,000 to a gain of $4,000,000. Interacting groups of 3 or 4 subjects produced a higher P choice reversal rate than did individuals. Individuals produced a somewhat lower preference reversal rate in the managerial task than in an individual task in which the outcomes were reduced by a factor of about 10,000.

Tversky and Slovic (1984) and Goldstein and Einhorn (1986) also replicated the preference reversal effect. Both studies found that the rate of preference reversal is increased when the choice task is replaced with a task in which subjects are instructed to judge bets on a relative "attractiveness" scale. In addition, both papers presented axiomatic models of subjects' responses in preference reversal experiments. Both models were shown to provide an excellent fit.

Berg et al. (1985) administered a preference reversal task in which they attempted to elicit bids such that the subject was indifferent between buying and selling the bet. They then used an arbitrage procedure to exploit P choice reversals. Subjects who committed P choice reversals were forced to buy, trade and sell according to their stated preferences and bids. Through this procedure, these subjects lost part or all of an initial $7 stake they had been given. A second preference reversal task was then administered. In comparision with the first task, the P choice reversal rate did not change, but the average magnitude of reversals decreased. It appears that the arbitrage procedure caused subjects to make generally smaller bids. There is no indication that the procedure had a differential effect on bids for P bets and $ bets.

The Satisficing Perspective

Overview

Fifteen years of research on preference reversal has yielded two widely accepted conclusions. First, the phenomenon is extremely robust; in the literature it is universal. Second, the phenomenon is caused by use of the anchoring and adjustment heuristic (or some formally similar mechanism) for setting bids.

The present work parts company with the literature on both of these points. First, it will be demonstrated that, not only can the frequency of occurrence of the standard preference reversal phenomenon be reduced, the sign of the effect can actually be reversed. Second, a simple and more general theoretical perspective will be proposed, which explains this dramatic shift in reversal rates, and which casts previous experimental work on preference reversal in an entirely new light. It will be shown that, when the task is shifted into a more meaningful realm, people are able to bring to bear a more sophisticated strategy for setting bids. This strategy will be defined as a form of satisficing (Simon, 1955). Satisficing will be

shown to result in a sensible, goal-driven pattern of preferences, which, nonetheless, involves a type of preference reversal.

The Precedence of Aspiration Level

For present purposes, the key characteristic of satisficing strategies is that they are driven by sensible, coherent underlying goals. In the context of decision under risk in a unidimensional outcome space, aspiration level is a goal that meets these requirements. Lopes (1984, in press) advanced a theoretical approach in which aspiration level is seen as the reference point around which the decision process is organized. For present purposes, aspiration level is defined as the minimum acceptable value on the outcome dimension. Aspiration level has been advocated as a crucial construct in the study of decision under risk, because it allows for outcomes to be evaluated differently depending on where they fall relative to the decision maker's current needs and expectations (Allais, 1952/1979; Lopes, 1984, in press; Siegel, 1957; Simon, 1955).

Aspiration level is a situation-specific variable which is primarily a function of the individual's present needs and of what the available alternatives have to offer (Lopes, in press). Present needs reflect new or existing environmental demands on the individual's resources. For example, a student who is considering ways of making an overdue $250 rent payment in order to avoid eviction probably has an aspiration level of $250. In this extreme example, the aspiration level is determined solely by environmental demands. The dependence of aspiration level on the characteristics of the available alternatives implies that a given risky option may be evaluated differently depending on the set of competing options. Although their results cannot be attributed directly to variation in aspiration level, Fryback, Goodman and Edwards (1973) created large and reliable context effects by manipulating the set of competing options. These context effects violate nearly all descriptive decision theories, especially when the number of alternatives is greater than two.

In the present context, satisficing is the process of choosing an alternative (or making a bid) which gives only a small, or the smallest, probability of failure to meet or exceed the aspiration level. Thus it is predicted that a course of action will be chosen which gives a good chance of "coming out ahead" or, at least, "breaking even" with respect to the aspiration level. Lopes (1981) argued that this criterion not only describes human behavior, but that its prescriptions are sometimes more reasonable than those of expected utility theory. Although people probably consider other factors besides the probability of achieving the aspiration level, additional theoretical complexity is not needed for the present development.

Satisficing in Preference Reversal Experiments

Satisficing in maximum buying price tasks. In this section, a satisficing hypothesis will be defined which makes a critical prediction for preference reversal tasks in which bids are elicited in the form of maximum buying prices. This prediction is the exact opposite of that made by the anchoring and adjustment hypothesis. Payne, Laughhunn and Crum (1980) reported an experiment which did not deal with the preference reversal phenomenon, but which nonetheless provided the seed for this critical prediction. They showed that reliable changes in preference in a choice task can be induced by subtracting a constant from all outcomes of a set of alternative bets. Moreover, they explained these changes in terms of the

relationships between outcomes and the aspiration level.

How might the goal to meet or exceed the aspiration level affect bidding under maximum buying price instructions? The answer depends primarily on the value of the maximum acceptable probability of failure to meet/exceed the aspiration level. This probability will be referred to as p_{max}. p_{max} is fundamental, because, for semi-continuous outcome distributions, as this probability increases (decreases), the aspiration level is free to increase (decrease). (This dependency holds for bets with as few as two outcomes, but the predictions become more coarse as the number of outcomes decreases.) Thus, the aspiration level will be set subject to the constraint that the resulting probability of failure to meet/exceed the aspiration level not exceed p_{max}. Measurement of p_{max} for all combinations of subjects and bets is unnecessary for present purposes. It will be shown that, whenever p_{max} is fairly small (i.e., less than approximately .5) in the bidding task, and is greater in the choice task than in the bidding task, a new reversal pattern is predicted in which P choice reversal is the exception and $ choice reversal the rule.

To simplify the development, it will be assumed that subjects set their buying prices by setting them equal to the aspiration level. This is identical to assuming that the aspiration level, in terms of net outcomes after subtraction of the buying price, is the status quo ($0 gained and $0 lost). (Hereafter, aspiration level in terms of net outcomes will be referred to as <u>net aspiration level</u>.) This assumption is made frequently when, as is the case in the bidding task, gains and losses relative to the status quo are both possible (Fishburn & Kochenberger, 1979; Kahneman & Tversky, 1979; Payne, 1980). The major conclusions of this paper appear to be robust to violation of this assumption.

If p_{max} is not large and the net aspiration level is the status quo, then subjects will satisfice in the maximum buying price task by setting bids as high as possible without incurring large probabilities of net out-of-pocket losses. This general prediction leads to a more specific prediction which is the crux of the theoretical development. This prediction is that <u>P bets will receive higher bids than $ bets</u>. The following examples elaborate the underlying reasoning.

Figure 1 shows two multi-outcome bets in the form of lotteries. Each tally mark represents a lottery ticket. Each lottery has 100 tickets and an expected value of approximately $100. The dollar amount at the left of each row represents the prize that is attached to each of the tickets in that row. For each row, the number in parentheses indicates the number of tickets in the row. The top lottery has two tickets that pay $455, two tickets that pay $420, and so forth, down to 34 tickets that pay nothing. The bottom lottery has 34 tickets that pay $128, 20 tickets that pay $118, and so forth, down to two tickets that pay nothing.

The top lottery will be considered a $ bet and the bottom lottery a P bet. For the $ bet, a bid in excess of $35 would probably result in a net loss. Thus, according to the satisficing hypothesis, such a bid would be too large--too "risky." However, for the P bet, a bid of $108 or less would probably result in a net gain. Thus a bid of $108 for the P bet might be satisfactorily "safe." For the $ bet, a bid greater than $0, but less than or equal to $35 would give a .34 probability of a net loss. However, for the P bet, a bid of $89 or less would give less than a .34 probability of a net loss. Thus, a person willing to accept no more than a one-third chance

of a net loss could bid as much as $89 for the P bet, but would have to bid nothing for the $ bet. For the Figure 1 bets, the satisficing hypothesis predicts clearly that people will bid more for the P bet than for the $ bet. This prediction holds even if it is assumed that the bidder is willing to incur as much as a .66 probability of a net loss (p_{max} less than or equal to .66). For any P and $ bet pair, the critical value of p_{max} above which the $ bet is predicted to receive a higher bid than the P bet can be found graphically by comparing the two bet's cumulative probability distributions Lopes (1984).

The same reasoning can be applied to two-outcome bets. Figure 2 shows a two-outcome $ bet and a two-outcome P bet. These bets have the same format, minimum and maximum outcomes, and expected values as the respective Figure 1 bets. Suppose the maximum acceptable probability of a net loss were greater than or equal to .22, but less than .78. If bids are maximized subject to this constraint, the P bet will receive a higher bid than the $ bet. If .22 were considered to be an unacceptably high probability of a net loss, then, technically, $0 should be bid for both bets. However, rather than bid exactly $0, an individual might bid for each bet according to the maximum net loss that could be tolerated given the probability of a net loss offered by the bet. The resulting bid for the P bet should be greater than that for the $ bet.

The precise value of p_{max} below which the P bet is predicted to receive the larger bid depends upon the combined characteristics of the particular pair of bets. For the bet pairs used as stimuli in the experiments to be reported, this probability ranged from .44 to .99.

Satisficing in the choice task. In order to predict fully whether preferences will be consistent or will reverse between the choice and maximum buying price tasks, it is important to consider how people behaving in accord with the satisficing hypothesis will choose between the two bets. Although the satisficing hypothesis predicts that, when p_{max} is small, the P bet will always receive a higher bid, no prediction is possible concerning whether P bets or $ bets will be chosen more often. Depending upon _how much_ larger p_{max} is in the choice task than in the bidding task, either bet may be chosen. If it is only slightly larger, the P bet may be preferred, just as in the bidding task. In contrast, if p_{max} is near 1.0 in the choice task, the aspiration level may actually be set higher than the P bet's maximum outcome. In this case the $ bet would be chosen. The choice task aspiration level may, of course, vary from choice to choice depending on the combination of characteristics of each pair of bets.

A powerful prediction can be made, however, anytime p_{max} tends to be _greater_ in the choice task than in the bidding task. To the extent that out-of-pocket costs are more-to-be-avoided than "opportunity" costs, this condition is likely to be met. If people are willing to accept a greater chance of failing to reach the aspiration level in win-only tasks than in tasks in which losses are also possible, then they will be more likely to choose the $ bet than to bid more for the $ bet.

The role of aspiration level in determining bids and choices is easier to see and appreciate for multi-outcome bets than for bets having only two outcomes. However, the same predictions apply in the two-outcome case. Consider the choice between the Figure 2 bets. If the aspiration level is less than or equal to $128, the P bet will be chosen. If the aspiration

level is greater than $128 (e.g., $455), the $ bet will be chosen.

Predictions: Satisficing versus anchoring and adjustment. Figure 3 contrasts the predictions of the satisficing and anchoring and adjustment hypotheses in terms of the four possible choice versus bid preference patterns. In cells A and C the P bet receives a higher bid, while in cells B and D the $ bet receives a higher bid. According to the satisficing hypothesis, regardless of which bet is chosen, the P bet will receive a higher bid. Thus, when the $ bet is chosen, the P bet should receive a higher bid (cell C). This is the new reversal pattern predicted by satisficing. Also, contradictory to the anchoring and adjustment hypothesis, when the P bet is chosen, it should also receive a higher bid (cell A). Thus individuals acting in accord with the satisficing hypothesis should not generate the standard preference reversal pattern.

Recall that according to the anchoring and adjustment hypothesis people set bids by anchoring on the amount to win and adjusting insufficiently to take into account the probability of not winning. Since more adjustment is needed for the $ bet for the P bet, the $ bet is overpriced relative to the P bet. Therefore, in its strongest form, the anchoring and adjustment hypothesis predicts that the $ bet will always receive a higher bid than will the P bet. Thus when the P bet is chosen, the $ bet will receive a higher bid (cell B). When the $ bet is chosen, it should also receive a higher bid (cell D).

The empirical state of affairs that would favor the satisficing hypothesis would be a high $ choice reversal rate coupled with a low P choice reversal rate. In contrast, a low $ choice reversal rate and a high P choice reversal rate defines the standard preference reveral phenomenon and would favor the anchoring and adjustment hypothesis. Equal reversal rates would favor neither hypothesis.

Review of Maximum Buying Price Preference Reversal Experiments

To date, three preference reversal experiments have been reported that employed maximum buying price instructions. In all three experiments the reversal rates favored the anchoring and adjustment hypothesis over the satisficing hypothesis. Although none of these experiments were designed explicitly to test the satisficing hypothesis, the requirements for a critical test were nonetheless met by each. In their Experiment 2, Lichtenstein and Slovic (1971) used two-outcome bet pairs in which the amount to win ranged from $.10 to $10 and the expected value ranged from $.10 to $3.70. Consistent with the anchoring and adjustment hypothesis, 70 percent of subjects produced a higher rate of P choice reversal than of $ choice reversal.

Hamm (1979) ran subjects individually in a carefully controlled experiment which involved administration of the choice and bidding tasks before and after a directed discussion intended to affect reversal rates by altering subjects' strategies. The nature of the discussion was a between subject manipulation. Subjects were advised to attend more to the values or the probabilities of the bets, or advised to take a more analytic or a more intuitive approach. Before discussion, the P choice reversal rate was .48 and the $ choice reversal rate was .28. None of the discussion conditions produced a decrease in the P choice reversal rate. The post-discussion reversal rates averaged across conditions were .48 for P choice and .18 for

$ choice.

Weber (1984) used three-outcome bets in addition to the same two-outcome bets that were used by Lichtenstein and Slovic (1971) in their Experiments 1 and 3. The three-outcome bets were created by double-play transformations on the two-outcome bets. Subjects participated in three replications of the choice and bidding tasks in three separate sessions. For the third replication, subjects reviewed their bids and choices from the first two replications and then made final, binding choices and bids. For two-outcome bets the standard preference reversal phenomenon was found. Twelve subjects showed a higher rate of P choice reversal than $ choice reversal and only one subject showed the opposite pattern. For three-outcome bets, six subjects showed the standard pattern and three showed the opposite pattern. Analyzed in this way, the preference reversal effect for three-outcome bets was not significant. In addition, there were significantly more P choice reversals in the two-outcome condition than in the three-outcome condition.

The preference reversal effect for three-outcome bets might have been significant had the sample size been larger. P choice reversals were more frequent than $ choice reversals for three-outcome bets, but not significantly so. Nevertheless, Weber's results raise the possibility that preference reversal occurs less frequently when alternatives have more than two outcomes.

The results of these maximum buying price experiments support the anchoring and adjustment hypothesis and refute the satisficing hypothesis, especially for two-outcome bets. Experiment 1 of the present paper was designed to overcome some difficulties with these experiments which may have caused satisificing to play a reduced role in the bidding tasks.

Experiment 1

The major differences between Experiment 1 and the maximum buying price experiments reviewed above were that, in Experiment 1:

1. Multi-outcome bets having up to 20 outcomes were employed in addition to two-outcome bets.

2. All bets had expected values of $95 to $110 (instead of less than $5.00).

3. Prior to the bidding task, a brief example was provided in which a bet was translated to reflect the possible net outcomes given that a fixed amount had been paid for the bet.

The effect of the first change was examined in Experiment 1. The effects of the other two changes were examined in Part 1 of Experiment 2. These changes will now be discussed in turn.

Using expected values of $95-$110 results in nearly all bets having at least one outcome greater than $100, whereas in previous maximum buying price experiments, almost all outcomes have been less than $10. If preference reversal is frequent only when the stakes are small, then its financial consequences are not devastating and the phenomenon may turn out to be simply the result of a handy short-cut. The only previous study which used outcomes similar in magnitude to those of Experiment 1 (Pommerehne et

al., 1982) was not a critical test of the satisficing hypothesis, because bids were elicited as minimum selling prices, not as maximum buying prices.

Multi-outcome bets were used in addition to two-outcome bets for several reasons. First, many important decisions in everyday life have outcomes which can vary over a range of values (Lopes, in press). Due to this characteristic of the environment, people may be better equipped to deal with multi-outcome distributions than with two-outcome distributions. Second, the role of aspiration level is clearer for multi-outcome bets than for two-outcome bets (Lopes, 1984). Finally, in multi-outcome bets, the amount to win is represented by a range of values instead of by a single point. Thus, although it is possible to imagine various ways that bids for multi-outcome bets could be set by anchoring and adjustment, multi-outcome bets may reduce the P choice reversal rate by reducing the tendency to anchor on the maximum payoff.

The final change in Experiment 1 was the inclusion of an instruction intended to encourage subjects to think of their bids in terms of the possible net outcomes. The instruction referred to a two-outcome P bet similar to the one in Figure 2. Subjects were told to suppose that they had paid $X for the bet. They were then told that, depending upon the outcome of the bet, they would end up with either a win of $(154-X) or an out-of-pocket loss of $X. The rationale for this instruction comes from the theoretical analysis of the cognitive operations involved in satisficing in maximum buying price tasks. This analysis is presented in Part 2 of Experiment 2.

<u>Method</u>

<u>Stimuli</u>. Twelve bet pairs were used in Experiment 1. All followed the same format as those in Figures 1 and 2. Each bet pair consisted of a P bet and a $ bet. Each bet had a minimum outcome of $0. The approximate expected values were $95 (range: $94.48-$95.20) for the P bets and $110 (range: $109.91-$110.22) for the $ bets. The $ bets were given larger expected values than the P bets in an attempt to equate the choice frequencies for the two types of bets. For two-outcome $ bets the probabilities of winning ranged from .15 to .50 in .07 steps. For two-outcome P bets the probabilities of winning ranged from .65 to .98. Thus the winning amounts ranged from $97 to $146 for P bets and from $220 to $733 for $ bets. An attempt was made to pair two-outcome $ bets and P bets in such a way that the ratio of the amount to win in the $ bet to the amount to win in the P bet would vary from pair to pair. This ratio ranged from 1.69 to 4.33. The six pairs of two-outcome bets are shown in Table 1.

The stimulus set consisted of six pairs of two-outcome bets and six pairs of multi-outcome bets. For each two-outcome bet pair a matching multi-outcome bet pair was created. Bets were matched in terms of their largest outcome. The multi-outcome bets differed from the two-outcome bets in that, in the former, the probability mass was distributed across the interval from $0 to the largest outcome. The multi-outcome bets had from four to 20 outcomes each and were similar to the skewed distributions used by Lopes (1984).

Bet pairs were presented to subjects in one of three random orders. For the choice task, the bet pairs were presented in a 14 page booklet which had one pair on each page. The first two bet pairs in the booklet (one two-outcome pair and one multi-outcome pair) were for practice and responses to these pages were not analyzed. Within the booklet, every other page

contained a multi-outcome bet pair. A two-outcome pair and its matching multi-outcome pair never appeared on consecutive pages.

For the bidding task, bets were presented in a 26 page booklet which had one bet on each page. Each subject received one of three random orders. As in the choice task, the first two pages of the booklet were for practice. Within the booklet, no more than two bets of the same type (two-outcome or multi-outcome) appeared consecutively. A two-outcome bet and its matching multi-outcome bet never appeared on consecutive pages.

Design and Procedure. Although the manipulations of theoretical interest were within subject, a between subject control factor was also included. Subjects in the group condition were run in groups of two to six. Each subject in this condition read the instructions silently and worked independently. Subjects in the individual condition were run individually and the instructions were read aloud by the experimenter. Otherwise, the stimuli and procedure for the two conditions were identical. This between subject factor was included because, in most preference reversal experiments, subjects have been run in groups.

The instructions began with an explanation of the example lotteries and the choice task. Subjects were told to think over each choice until they were certain which lottery they would choose if the situation were real. It was emphasized that there were no right or wrong answers and that the subject's opinions were the data of interest. Subjects were instructed to work through the booklet sequentially and not to skip ahead or back. No time limit was imposed. Subjects were encouraged to ask questions at any time.

When the subject had completed the choice task, the instructions for the bidding task were given. The maximum buying price task was explained in detail. In order to discourage strategic behavior, subjects were told respond with their "top dollar" prices, as opposed to "make-me-an-offer" prices. Prices were constrained to being whole dollar amounts. For both the choice and bidding tasks, subjects recorded their responses on a separate response sheet according to booklet page number. The booklet and response sheet for the choice task were removed from subjects' view prior to the bidding task.

Subjects. The subjects were 72 students (36 per condition) taking an introductory psychology course. Subjects received extra credit to be applied to their course grades.

Results and Discussion

For each of the 12 bet pairs the number of subjects producing each possible choice versus bid preference pattern was determined. For any given bet pair six different patterns were possible. A subject could choose either the P bet or the $ bet and could bid more for the P bet, more for the $ bet, or equally for both bets. Tied bids imply neither reversal nor consistency between bids and choices. Therefore, for both experiments, the analyses to be reported exclude tied bids and the corresponding choices. In this experiment, 11 percent of the obtained bid versus choice patterns contained tied bids.

The results for the group condition will be reported in detail, since the method for this condition is the most comparable to that of Experiment 2. The results for the individual condition will then be sketched briefly

and compared to those for the group condition.

For the group condition, as predicted by the satisficing hypothesis, the \$ choice reversal rate was found to exceed the P choice reversal rate whether the rates were computed across subjects or across bet pairs. The P choice reversal rate was computed for each bet pair by dividing the number of subjects who produced a P choice reversal by the number of subjects who chose the P bet. The \$ choice reversal rate was computed in an analogous manner. For all 12 bet pairs, the \$ choice reversal rate exceeded the P choice reversal rate. This result was significant ($p<.01$). All significance tests to be reported are two-tailed binomial exact tests.

Three subjects never chose the \$ bet and one subject never chose the P bet. Therefore, the following results are based on the remaining 32 subjects. For each of these subjects, the P choice reversal rate was computed by dividing the number of bet pairs for which the subject produced a P choice reversal by the number of bet pairs for which the subject chose the P bet. The \$ choice reversal rate was computed analogously. Twenty-eight subjects showed a higher \$ choice reversal rate than P choice reversal rate and two subjects showed the opposite pattern. (Two subjects' reversal rates were equal.) As predicted by the satisficing hypothesis, significantly more subjects showed a higher \$ choice reversal rate than showed a higher P choice reversal rate ($p<.01$). The P choice and \$ choice reversal rates pooled over subjects and bet pairs for the group condition are shown in the top row of Table 2. There were no systematic differences between the reversal rates for two- and multi-outcome bets.

The decision to compute reversal rates by conditionalizing on choices rather than on preferences implied by bids is somewhat arbitrary (Hamm, 1979). However, the patterns reported above did not change when the data were re-analyzed by conditionalizing on bids.

The P bet was chosen 71 percent of the time for two-outcome bet pairs and 53 percent of the time for multi-outcome bet pairs. In five of six cases, the P bet was chosen more often for the two-outcome bet pair than for its corresponding multi-outcome bet pair. This result was not significant.

The major result for the individual condition was that, as in the group condition, the satisficing hypothesis was strongly supported. For the individual condition, pooling over subjects, the \$ choice reversal rate exceeded the P choice reversal rate for all 12 bet pairs ($p<.01$). Pooling over bet pairs, for 28 subjects the \$ choice reversal rate exceeded the P choice reversal rate, but only two subjects showed the opposite tendency ($p<.01$). There was relatively little difference between the reversal rates for the group and individual conditions. However, a somewhat surprising result, was that for 10 of the 12 bet pairs the P choice reversal rate for the group condition was smaller than that for the individual condition ($p=.04$). The \$ choice reversal rates did not differ significantly. Reversal rates pooled over subjects and bet pairs for the individual condition are shown in the bottom row of Table 2.

Experiment 2

Experiment 1 demonstrated for the first time the new, opposite reversal pattern predicted by the satisficing hypothesis. This demonstration raises two important, interrelated questions that are the focus of the remainder of

the paper. First, comparing the method of Experiment 1 to those of previous studies, which of the task modifications introduced in Experiment 1 catalyzed this dramatic shift in reversal rates? The answer may suggest how general the new reversal pattern is likely to be relative to the standard reversal pattern. The individual condition of Experiment 1 showed that the new reversal pattern is robust to superficial procedural changes. Thus, perhaps some more basic aspect of the task was responsible for engagement of the satisficing strategy. Of the three major modifications included in Experiment 1, use of multi-outcome bets can be eliminated as a possible catalyst of satisficing, because the new reversal pattern occurred for both two- and multi-outcome bets. Setting aside the possibility of interactions among subsets of the modifications, the only potential catalysts that remain are use of larger outcomes and the instruction emphasizing net outcomes[1,2].

Second, what benefits, if any, might result from the ability to generate bids by anchoring and adjustment in some situations and by satisficing in others? This question requires consideration of how the cognitive operations required to produce data supporting the satisficing hypothesis differ from those necessary to produce data supporting the anchoring and adjustment hypothesis. Specifically, is one strategy more cognitively taxing than the other?

Experiment 2 consisted of two parts. Part 1 examined the effect of outcome magnitude ("small" versus "large") on which reversal pattern predominates. The effect of the net outcome instruction was also examined. In Part 2, a task based on theoretical analysis of the cognitive processes involved in satisficing was used to show that the standard preference reversal pattern can give way to the new reversal pattern even for bets with small outcomes (i.e., expected value less than $5).

Part 1: Effect of Small Versus Large Outcomes

In creating the bets for Experiment 1 the intent was to make the outcomes large enough to be highly salient to college student subjects, but small enough that the typical subject has had experience making decisions concerning similar amounts. The belief underlying use of more substantial outcomes is that individuals do not typically care to achieve perfect consistency in decisions where relatively small amounts of money are concerned. Most people are not in the habit of carefully scrutinizing and fine-tuning decisions which have outcomes that are "down in the noise" in terms of their overall wealth. As a result, it may be difficult to treat such decisions as though they are of paramount importance, even if the experimental instructions call for this frame of mind.

If the use of more substantial outcomes is critical to engagement of satisficing, then the preference reversal phenomenon may need to be recast as the result of a strategy which is, in some sense, optional. Moreover, such a finding would bring into question the generality of the phenomenon where important decisions are concerned.

Part 1 of Experiment 2 examined the effect of bets with "large" outcomes, similar in magnitude to those of Experiment 1, versus bets with "small" outcomes, similar in magnitude to those of most previous preference reversal work. The prediction was that, if substantial outcomes are needed to catalyze the satisicing process, then the small outcome condition should replicate the standard reversal pattern obtained in all previous studies,

while the large outcome condition should replicate the new reversal pattern obtained in Experiment 1.

In the small outcome condition of Part 1, the bets had expected values which were centered as closely as possible around the mean expected value of the bets used by Lichtenstein and Slovic (1971) in their Experiments 1 and 3 and in numerous other studies ($2.60). In the large outcome condition, the bets' expected values were centered around $100. In this condition, the bets were identical to those in the small outcome condition except that all outcomes were multiplied by a factor of about 38.

Only two-outcome bets were used in Experiment 2, because multi-outcome bets were found in Experiment 1 to make no difference in reversal rates, and because the probability equivalence task of Part 2 is applicable only to two-outcome bets. The expected values of the P and $ bets for the large outcome condition were more widely separated than those of the bets used in Experiment 1. This change was intended to force the choice proportions for P and $ bets to be more nearly equal.

<u>Method</u>

<u>Stimuli</u>. Twelve small and 12 large two-outcome bet pairs were created. The complete set of 24 bet pairs is shown in Table 3. The expected value was approximately $2.20 (range: $2.16-$2.24) for small P bets and $3.00 (range: $2.99-$3.01) for small $ bets. As in Experiment 1, all of the bets used in Experiment 2 had $0 as their minimum outcome. The probabilities of winning ranged from .50 to .99 for P bets and from .01 to .50 for $ bets. The large bets were obtained from the small bets by multiplying the (unrounded) outcomes of each of the small bets by 38.46. Thus the expected value was approximately $84.62 (range: $83.70-$86.40) for large P bets and $115.38 (range: $114.70-$115.50) for large $ bets. The outcomes were rounded to the nearest $0.10 for P bets and to the nearest $5.00 for $ bets. Small P bets were paired randomly with small $ bets. The same random pairing was used for the corresponding large bets.

<u>Design and Procedure</u>. Outcome magnitude (small versus large) was a between subject factor. A third group was included as a control. The stimuli and procedure for this group were identical to that for the large outcome group, except the instruction intended to draw attention to the manner in which bids alter net outcomes was omitted. (This instruction was described under Experiment 1.) As in Experiment 1, bet pair and choice versus bidding task were within subject factors.

Subjects were run individually or in groups of up to six and the instructions were presented in written form. Maximum buying prices were not constrained to be whole dollar amounts. Otherwise the procedure was identical to that of Experiment 1.

<u>Subjects</u>. The subject population was the same as for Experiment 1. There were 36 subjects in each of the three groups. Subjects in the large and small outcome conditions participated in Part 1 and returned at a later date for Part 2. Subjects in the control condition participated only in Part 1.

<u>Results and Discussion</u>

The effect of the outcome magnitude manipulation was striking: The small outcome condition replicated the standard preference reversal pattern, while the large outcome condition replicated the new, opposite reversal

pattern obtained in Experiment 1. For the small outcome condition, pooling over bet pairs, 32 of 32 subjects had higher P choice reversal rates than \$ choice reversal rates, as predicted by the anchoring and adjustment hypothesis. (Four subjects never chose the P bet.) Likewise, pooling over subjects, the P choice reversal rate exceeded the \$ choice reversal rate for all 12 small outcome bet pairs.

For the large outcome condition the opposite was found. In this condition, for 25 of 32 subjects the \$ choice reversal rate exceeded the P choice reversal rate ($p<.01$). (Two subjects had equal reversal rates and two never chose the \$ bet.) Likewise, the P choice reversal rate exceeded the \$ choice reversal rate for all 12 large outcome pairs ($p<.01$).

The overall reversal rates for all three conditions (small outcome, large outcome and control) are shown in the left half of Table 4. These reversal rates were obtained by pooling over subjects and bet pairs. The reversal rates for the control condition were virtually identical to those for the large outcome condition. Thus the instructional manipulation emphasizing the role of net outcomes had no significant effect. This result is not surprising in view of the subtlety of the manipulation.

The P bet was chosen in 68 percent of cases for the large outcome condition and in 43 percent of cases for the small outcome condition. The percentage of choice versus bid response patterns omitted from the analysis due to tied bids was 15 for the small outcome condition and 16 for the large outcome condition.

Part 2: "Translation" and Satisficing for Small Outcome Bets

The finding that the standard reversal pattern occurs for small outcome bets, but not for large outcome bets raises the possibility that anchoring and adjustment is a cognitive short-cut strategy that is used when motivation to make the best judgments is low. This possibility is also suggested by the fact that the new reversal pattern is normatively more acceptable than the standard reversal pattern. The standard reversal pattern has no rational basis (except in the second-order sense that anchoring and adjustment may be useful as a short-cut strategy). In contrast, the new reversal pattern is coherent in that it apparently results from a single strategy, satisficing based on an aspiration level, which is applied in both the choice and bidding tasks. The shift in aspiration level that underlies the new reversal pattern reveals a lack of formal equivalence between the choice and maximum buying price tasks. Thus, in practical terms, the new reversal pattern does not violate the invariance criterion of rational choice discussed earlier. People have purposefully different goals in the two tasks. In the choice task, the goal is to make a substantial profit, while, in the bidding task, the foremost goal is to avoid a net loss.

In what follows, a plausible operationalization of the satisficing strategy for bidding is described and a critical operation singled-out. It will be shown that whether this operation is executed potentially determines which hypotheses' predictions are realized. In Part 2 an indirect bid elicitation technique was used which removed any burden of executing this step. The prediction was that helping subjects over this cognitive "hump" should result in increased support for the satisficing hypothesis, especially for small outcome bets.

The idea that anchoring and adjustment is a useful short-cut strategy for setting bids assumes that satisficing is the more cognitively taxing of the two strategies. Therefore, it is important to consider what sorts of information processing sequences will produce bids consistent with the satisficing hypothesis and how these sequences compare to the anchoring and adjustment strategy in terms of complexity. It is also of interest to consider how each possible satisficing sequence might go awry and produce bids consistent with the anchoring and adjustment hypothesis. If, with slight modification, a single process can produce either type of reversal pattern, then it is not necessary to postulate a second-order cognitive "toggle switch" that weighs costs and benefits and selects one of two unrelated strategies.

Two basic strategies are logically possible for setting bids consistent with the satisficing hypothesis. The simplest strategy is one in which the value of p_{max} is set in advance and is constant for all bets. The bid is set by cumulating probability mass beginning with the probability associated with the smallest outcome and terminating when the largest outcome is found such that the cumulative probability up to and including that outcome is less than or equal to p_{max}. This outcome is the maximum buying price.

It is not clear that this strategy would be substantially more taxing than the anchoring and adjustment strategy, especially when the number of outcomes is small. In fact, unless p_{max} is extremely large, this strategy does not even process bets' largest outcomes. Thus it is difficult to imagine any way in which this strategy could go awry and produce data consistent with anchoring and adjustment. Of course, under this strategy, p_{max} (and, therefore, the aspiration level) is insensitive to the particular characteristics of each bet. Because of this insensitivity, this strategy is inconsistent with Lopes (in press) description of aspiration level.

Cumulating probability mass may not be the first strategy that comes to mind when one encounters the maximum buying price task. At the most superficial level, the task is to generate a number between the bet's minimum and maximum outcomes. At this level, probability considerations are secondary. It is far more plausible that subjects begin with an intuitive "ball-park" estimate of what they would be willing to pay for the bet or of what they would aspire to win from the bet. A satisficing rule might then be used to determine whether the estimate needs to be adjusted up, down, or not at all. This strategy and its implications will be described in the next section.

An Iterative Satisficing Strategy for Setting Bids

The second type of strategy which will generate data consistent with the satisficing hypothesis is one in which a satisficing rule is used to screen bids, rather than to create them from scratch. Figure 4 shows a flow diagram of how maximum buying prices may be generated. The solid-lined components represent the basic iterative satisficing strategy. This strategy, which involves three major steps, would clearly be more cognitively taxing than simple anchoring and adjustment. The first step is to set a tentative "ball-park" bid by whatever means. For example, consider a bet which offers a .1 chance of \$100 and a .9 chance of \$0. A tentative bid might, in principle, be set randomly within a range of amounts the player could afford to lose (e.g., \$1 to \$20). Alternatively, a tentative bid might actually be set by anchoring on \$100 and adjusting downward to take into account the .9 probability of losing.

The second and third steps serve to screen the tentative bid according to the rule prescribed by the satisficing hypothesis. Assuming that the net aspiration level is the status quo, the terms "bid" and "aspiration level" are interchangeable, since the value of the bid is the minimum amount the bet must pay in order for the aspiration level to be reached. The second step is to re-code or translate the bet to reflect the net outcome distribution given the value of the tentative bid. The satisficing hypothesis implicitly requires this step (unless the probability cumulation strategy described above is used). Evaluating an outcome distribution with respect to an aspiration level (bid) entails re-coding each outcome as above or below the aspiration level. Functionally, this re-coding must be done by subtracting the bid from each outcome. This subtraction procedure will be referred to as translation[3]. The third step is to cumulate the probability mass on one side of the aspiration level (for multi-outcome bets only), determine whether the probability of failure to reach the aspiration level is acceptable and, if necessary, adjust the bid upward or downward[4].

If this iterative strategy is used, the second step, translation, likely determines whether the standard or the new reversal pattern is manifest. An experiment reported in a different context by Kahneman and Tversky (1984) illustrates nicely the pivotal role of the translation step. In this experiment, subjects were asked "would you accept a gamble that offers a 10 percent chance to win $95 and a 90 percent chance to lose $5?" They were also asked at another time "would you pay $5 to participate in a lottery that offers a 10 percent chance to win $100 and a 90 percent chance to win nothing?" These two questions are formally identical. However, the result was that, of the subjects who rejected the first opportunity, many accepted the second opportunity. (The opposite pattern of inconsistency was rare.)

This result cannot be explained by a simple shift in aspiration level since both situations involve potential net gains and losses. It is reasonable to assume that the status quo is the net aspiration level in both situations. In the first situation, it is stated explicitly that a $5 loss is possible. However, in the second situation, in order to evaluate the outcome distribution in terms of net outcomes, the translation step must be executed: The buying price of $5 must be subtracted from each outcome. Following the translation step, the representation of the second question is identical to that of the first and both questions should yield the same preference. If, however, the translation step were to be omitted, the expenditure of $5 and the outcome of the bet would be effectively represented as separate events. Given this representation, the second opportunity is more likely to be accepted than the first. In this case, acceptance of the second opportunity may reflect only a general openness to making a $5 purchase, not a willingness to incur a .9 probability of losing $5 out-of-pocket.

To see how the translation step could determine which reversal pattern is obtained, suppose that a maximum buying price is to be set for a bet which offers a .1 chance of $100 and a .9 chance of nothing. Suppose that a tentative bid of $20 is set (step 1 above) by anchoring and adjustment and that this price is inflated due to insufficient adjustment. At this point, the task is analogous to Kahneman and Tversky's second situation and the same line of reasoning applies. If the tentative bid is then screened by the satisficing strategy (steps 2 and 3 above), the result should be a downward adjustment which would set the stage for a $ choice reversal. If,

however, the translation step is not performed, the stage is set for a P choice reversal.

Omission of the evaluation and re-adjustment step (step 3) would have the same effect as omission of the translation step. However, there is no reason to believe one of these steps would be performed without the other. Thus, if the translation step is not performed, there is nothing new to evaluate. Likewise, it would be senseless to expend the effort of translation unless the output of this process were needed for evaluation.

The Probability Equivalence Task

Before proceeding, it is necessary to introduce the concept of a bet's probability equivalent. Consider a two-outcome bet in which the player will either win \$W or lose \$L. An individual's probability equivalent for this bet is defined as the smallest probability of winning for which the individual would be willing to play the bet. If the probability of winning were smaller than this value, the individual would prefer to pass up the bet, but if the probability were equal to or larger than this value, the individual would prefer to play the bet. (Technically, the probability equivalent is usually defined as a limiting value such that the individual is indifferent between playing the bet and abstaining.)

For Part 2 each subject's own maximum buying prices for a set of two-outcome bets were used to create a new, personalized set of bets for each subject. These new bets were created by subtracting the subject's bid for a bet from each of the bet's outcomes. Thus the translation step was performed for subjects. Subjects made a probability equivalence judgment for each of these translated bets. The probability equivalence judgments were used to compute a "corrected" bid for each bet. The corrected bid for a bet is the product of the original bid and the ratio of the probability equivalent to the original probability of winning.

As an example of how the translated bets were constructed and corrected bids computed, suppose a subject states a maximum buying price of \$80 for a \$ bet which offers a .22 chance of \$455 and a .78 chance of \$0. The personalized bet for the probability equivalence task is constructed by subtracting the bid from each of the bet's outcomes. The translated bet, then, offers a win of \$375 or a loss of \$80. This bet is presented without probability information and the subject's probability equivalent is elicited. Suppose the probability equivalent is .60. In this example, the probability equivalent is much higher than the original probability of winning. This relationship indicates that, contrary to the original bid, the subject would not be willing to risk \$80 for a .22 chance of \$455. The subject would be willing to risk as much as \$80 only if the probability of winning were increased to at least .60. The corrected maximum buying price would equal \$80(.22/.60) or \$29.33.

Rationale and Predictions

Part 2 of Experiment 2 provided a test of the joint proposition that the iterative satisficing strategy is responsible for the new reversal pattern and the standard reversal pattern occurs to the extent that the translation step is omitted. The rationale for the experiment is that, if bids could be obtained using an elicitation method which does not require subjects to perform the translation step in order to implement the satisficing strategy, then even for bets with small outcomes, reversal rates should favor the satisficing hypothesis.

The predictions for Part 2 are in terms of two sets of P and $ choice reversal rates that permit a "before and after" comparison. Just as before, "original" reversal rates are based on choices and maximum buying prices. "Corrected" reversal rates are based on the same choice data. However, the bids used to determine corrected reversal rates are the corrected bids computed from the probability equivalence judgments.

The general prediction is that any overpricing of $ bets relative to P bets should disappear when the need for subjects to execute the translation step is removed. Thus, the probability equivalence task should cause the P choice reversal rate to decrease and the $ choice reversal rate to increase, regardless of the original reversal rates. For tasks in which the original reversal rates support the anchoring and adjustment hypothesis (e.g., the small outcome condition of Part 1), the corrected reversal rates should favor the satisficing hypothesis.

Method

Stimuli. For the probability equivalence task, a personalized 26 page booklet was created for each subject by subtracting the subject's maximum buying price for each bet from both of the bet's outcomes. Each booklet page contained one bet. The first two bets in the booklet were for practice and were the same for all subjects. Responses to these bets were not analyzed. The remaining 24 bets (12 P bets and 12 $ bets) were ordered for each subject in one of three different random orders. Probability information was omitted from the bets.

Procedure. Subjects were instructed to record for each bet "the minimum number of lottery tickets out of 100 that would have to be winning tickets before you would be willing to risk drawing a ticket." The instructions were presented in written form. Subjects were not informed that the lotteries for Part 2 were created using responses from Part 1.

Results and Discussion

Using the procedure described above, the probability equivalence judgments obtained in Part 2 of Experiment 2 were used to correct the maximum buying price judgments from Part 1. This correction was performed for each subject-by-bet combination. The corrected maximum buying prices were then compared with the corresponding choices from Part 1 in order to arrive at corrected reversal rates. The right half of Table 4 shows the corrected reversal rates. The original values shown in the left half of Table 4 are, of course, based on Part 1 choices and Part 1 maximum buying prices. The corrected values are based on Part 1 choices and corrected (Part 2) bids.

Table 4 shows clearly that, as predicted, for both outcome magnitude conditions the probability equivalence judgments produced corrections in the direction of increased $ choice reversal and decreased P choice reversal. Thus, the bid corrections based on these judgments increased agreement with the satisficing hypothesis at the expense of the anchoring and adjustment hypothesis.

The shift in favor of satisficing was quite dramatic for the small bet condition, which initially showed overwhelming support for the anchoring and adjustment hypothesis. For 26 of 28 subjects the corrected P choice reversal rate was smaller than the original rate ($p<.01$). This relationship also held for 11 of the 12 bet pairs ($p<.01$). For 30 of 32 subjects the

corrected \$ choice reversal rate exceeded the original rate ($p<.01$). This relationship also held for all 12 bet pairs. Recall that, when original reversal rates were examined, the anchoring and adjustment hypothesis was supported for all bet pairs and virtually all subjects in the small bet condition. In direct contrast, analysis of corrected reversal rates revealed that a marginally significant proportion of subjects, 21 of 31 or 68 percent, showed higher \$ choice reversal rates than P choice reversal rates ($p=.07$). This relationship also held for 9 of the 12 bet pairs. However, this latter proportion was not significant ($p=.15$).

For the large bet condition, the corrected analysis revealed even stronger support for the satisficing hypothesis than was shown in the original analysis. A marginally significant proportion of subjects, 18 of 26 or 69 percent, showed smaller corrected than original P choice reversal rates ($p=.08$). This relationship also held for 9 of the 12 bet pairs. However, this latter proportion was not significant ($p=.15$). A significant proportion of subjects, 21 of 26 or 81 percent, had corrected \$ choice reversal rates that exceeded their original rates ($p<.01$). This relationship also held for 11 of 12 bet pairs ($p<.01$).

As predicted, when the task was designed so that the translation operation was performed in all instances, the reversal rates favored the satisficing hypothesis more strongly. This result reinforces the propositions that (1) subjects satisfice in the bidding task by using the iterative strategy, (2) whether the translation step is executed determines which hypothesis is instantiated, and (3) the satisficing strategy makes greater information processing demands than the anchoring and adjustment strategy.

The entirety of Figure 4 (including the dashed-line portions) shows the resulting model of how maximum buying prices are generated. Assuming tentative bids are set by anchoring and adjustment, this model predicts the standard reversal pattern when outcomes are small and the new reversal pattern when outcomes are substantial. In unimportant situations (e.g., the small outcome condition), the tentative bid is output prior to the translation step and the process terminates. In important situations (e.g., the large outcome condition), the tentative bid is screened by the iterative satisficing strategy and adjusted, if necessary, before being output.

General Discussion

The present results show for the first time that, when the outcomes of risky alternatives are substantial, the preference reversal phenomenon can reverse. The new and opposite reversal pattern is one in which subjects generally offer a larger maximum buying price for the P bet than for the \$ bet, regardless of which bet they preferred in the pairwise choice task. According to the satisficing/aspiration level view, this new reversal pattern is perfectly consistent and reasonable. In this view, the inconsistency is between the two ways the question is framed, not the two ways the question is answered. People intentionally orient their behavior around a different goal in the bidding task, which involves potential losses, than in the choice task, which does not.

Experiment 1 showed that the new reversal pattern is robust as the number of outcomes per bet is varied (from two to 20) and is robust to certain superficial procedural changes. Part 1 of Experiment 2 showed that

the magnitude of the bets' outcomes mediates which reversal pattern occurs. For large outcome bets (expected values near $100) the new reversal pattern occurs, but for small outcome bets (expected values near $3) the standard reversal pattern is obtained. In Part 2 of Experiment 2, a plausible iterative satisficing strategy for setting bids was developed. It was determined that, if this strategy underlies the new reversal pattern, then the critical step is translation of bets to reflect net outcomes given a tentative bid. Whether this implicit step is executed potentially determines which reversal pattern is obtained. A probability equivalence task which removed the need for this step was used to allow subjects to cross-check their bids. The result was that, with the need to translate removed, the new reversal pattern was obtained for small as well as large outcome bets.

The anchoring and adjustment hypothesis as a stand-alone theory of preference reversal is falsified by the demonstration of the new reversal pattern. However, even in terms of what it says about the cognitive processes that underlie the standard preference reversal pattern, the anchoring and adjustment hypothesis is misleading, if not altogether wrong. Its shortcoming is clear when one considers that it has provided the seed for some of the fruitless attempts to demonstrate limitations on the phenomenon (e.g., the manipulations employed by Hamm, 1979). The anchoring and adjustment idea suggests that the way to elminate P choice reversal is to induce people to place more weight on the probability of losing or less weight on the amount to win in the bidding task. In contrast, the satisficing hypothesis suggests that omission of the translation step is the source of the difficulty and, indeed, when this step was done for subjects in Experiment 2, Part 2, the standard preference reversal pattern gave way to the new reversal pattern. Thus, the anchoring and adjustment hypothesis provides a quite incomplete picture. The standard preference reversal pattern is not the result of insufficient adjustment per se. Rather, when the translation step required by satisficing is omitted, there is nothing to prevent generation of responses consistent with anchoring and adjustment.

Conclusion

The model shown in Figure 4 provides a new theoretical and practical perspective on the preference reversal phenomenon. Theoretically, whether the standard preference reversal pattern is obtained in a given situation depends upon whether the iterative satisficing strategy, including the translation step, is performed. This view differs greatly from previous accounts which have implicated only an anchoring and adjustment or compatibility mechanism.

The following four propositions, all of which are supported by the present data, provide a new perspective on preference reversal at a more practical level:

1. The standard preference reversal pattern occurs in some instances and the opposite reversal pattern occurs in others.

2. The opposite reversal pattern is on more firm normative ground than the standard reversal pattern.

3. The processing strategy which underlies the opposite reversal pattern (satisficing based on an aspiration level) is more cognitively taxing than that which underlies the standard reversal pattern.

4. This more taxing strategy comes into play when the stakes are relatively large and motivation to make good judgments and decisions is correspondingly high.

It would be easy to draw the conclusion from the literature that the preference reveral phenomenon results from a "hard-wired" information processing limitation. However, these propositions indicate that a motivational "underload", and not an information processing overload, is the culprit. The picture that emerges is one of a contingent information processing system (Payne, 1982) which, for important decisions, operates primarily in a top-down, goal-driven mode. The standard preference reversal pattern, then, is relegated to the status of a by-product which results from an <u>optional</u> cognitive short-cut that is used when the potential outcomes are of minor consequence.

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Footnotes

1. An additional difference between the method of the present experiments and those of most previous preference reversal work is that the minimum outcomes of all bets in the present experiments were zero, rather than negative. Hamm (1979) and Lichtenstein and Slovic (1971) argued on theoretical grounds that the relationship between the negative outcomes of their P and $ bets had a contributory influence on the strength of the standard preference reversal pattern in their experiments. However, Goldstein and Einhorn (1986) showed that the P choice reversal rate is actually higher when all minimum outcomes are zero. Thus, use of bets with zero minimum outcomes in the present experiments should have, if anything, biased the results in favor of the anchoring and adjustment hypothesis. Indeed, the P choice reversal rate in the small outcome condition of Experiment 2, Part 1 was much larger than those obtained in Hamm's and Lichtenstein and Slovic's maximum buying price tasks.

2. Unlike Experiment 1, most preference reversal experiments have held expected value constant, or nearly constant, within bet pairs. However, the results of Experiment 1 were replicated in an experiment in which expected value was held constant (at $100) for all bets.

3. Payne (1980) used the term in a related way.

4. If the net aspiration level is greater than the status quo, then <u>two</u> translation steps must implicitly be performed. First, the amount of the tentative bid must be subtracted from each of the bet's outcomes. Second, the tentative aspiration level must be subtracted from each of the outcomes of the resulting bet. That is, each outcome must be re-coded relative to the aspiration level. The order of these two steps is immaterial.

Table 1

The Two-Outcome Bet Pairs Used as Stimuli in Experiment 1

Pair	Bet type	Probability of winning	Amount to win
1	P	.65	$146
	$	.15	$733
2	P	.72	$132
	$	.36	$306
3	P	.78	$122
	$	.22	$500
4	P	.85	$112
	$	.50	$220
5	P	.91	$104
	$	.29	$380
6	P	.98	$ 97
	$	.43	$256

Note. The expected values are approximately $95 for the P bets and approximately $110 for the $ bets.

Table 2

Experiment 1 P Choice and $ Choice Reversal Rates as a Function of Number of Outcomes and Condition

	Two-outcome bets		Multi-outcome bets		Overall	
Cond.	P Choice	$ Choice	P Choice	$ Choice	P Choice	$ Choice
Group	.17	.62	.21	.78	.19	.72
Indiv.	.23	.70	.22	.69	.22	.70

Note. The rates were obtained by pooling over subjects and bet pairs.

Table 3

The Large and Small Outcome Bet Pairs Used as Stimuli in Part 1 of Experiment 2

Prob. of Winning		Amount to win (in dollars) Small outcome condition		Large outcome condition	
P bet	$ bet	P bet	$ bet	P bet	$ bet
.50	.41	4.40	7.30	170	280
.54	.01	4.10	300.00	155	11540
.59	.46	3.70	6.50	145	250
.63	.23	3.50	13.00	135	500
.68	.10	3.20	30.00	125	1155
.72	.50	3.10	6.00	120	230
.77	.14	2.90	21.40	110	825
.81	.05	2.70	60.00	105	2310
.86	.19	2.60	15.80	100	605
.90	.37	2.40	8.10	95	310
.95	.28	2.30	10.70	90	410
.99	.32	2.20	9.40	85	360

Note. The expected values for the small outcome condition are approximately $2.20 for P bets and approximately $3.00 for $ bets. The expected values for the large outcome condition are approximately $85 for P bets and approximately $115 for $ bets.

Table 4

Experiment 2 Original (Part 1) and Corrected (Part 2) Reversal Rates as a Function of Outcome Magnitude

	Original (Part 1)		Corrected (Part 2)	
Condition	P Choice	$ Choice	P Choice	$ Choice
Small outcome	.85	.10	.31	.57
Large outcome	.20	.53	.09	.78
Control	.19	.54	--	--

Figure Captions

Figure 1. A pair of multi-outcome lotteries (bets) similar to those used as stimuli in Experiment 1. (The designations "$ bet" and "P bet" did not appear on the actual stimulus lotteries.)

Figure 2. A pair of two-outcome lotteries (bets) similar to those used as stimuli in Experiment 1.

Figure 3. The four possible choice versus bid combinations. If the P bet is chosen, but the $ bet receives a higher bid (cell B), a P choice reversal has occurred, as predicted by the anchoring and adjustment hypothesis. If the $ bet is chosen, but the P bet receives a higher bid (cell C), a $ choice reversal has occurred, as predicted by the satisficing hypothesis.

Figure 4. Flow diagram model of how maximum buying price bids are generated. The solid-lined portions comprise the basic iterative satisficing strategy described in Part 2 of Experiment 2.

Figure 1

$455	(2)	II	
$420	(2)	II	
$385	(2)	II	
$350	(2)	II	
$315	(3)	III	
$280	(3)	III	
$245	(3)	III	$ BET
$210	(4)	IIII	
$175	(4)	IIII	
$140	(5)	IIIII	
$105	(6)	IIIIII	
$ 70	(10)	IIIIIIIIII	
$ 35	(20)	IIIIIIIIIIIIIIIIIIII	
$ 0	(34)	IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII	

$128	(34)	IIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIII	
$118	(20)	IIIIIIIIIIIIIIIIIIII	
$108	(10)	IIIIIIIIII	
$ 99	(6)	IIIIII	
$ 89	(5)	IIIII	
$ 79	(4)	IIII	
$ 69	(4)	IIII	
$ 59	(3)	III	P BET
$ 49	(3)	III	
$ 39	(3)	III	
$ 30	(2)	II	
$ 20	(2)	II	
$ 10	(2)	II	
$ 0	(2)	II	

Figure 2

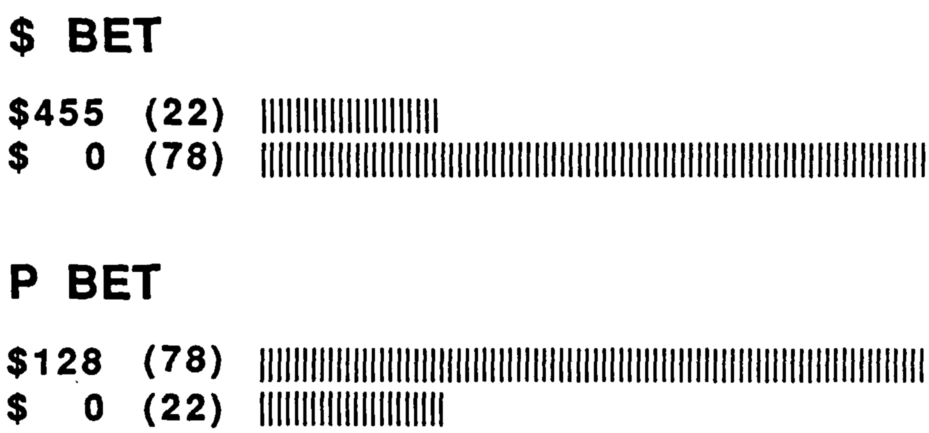
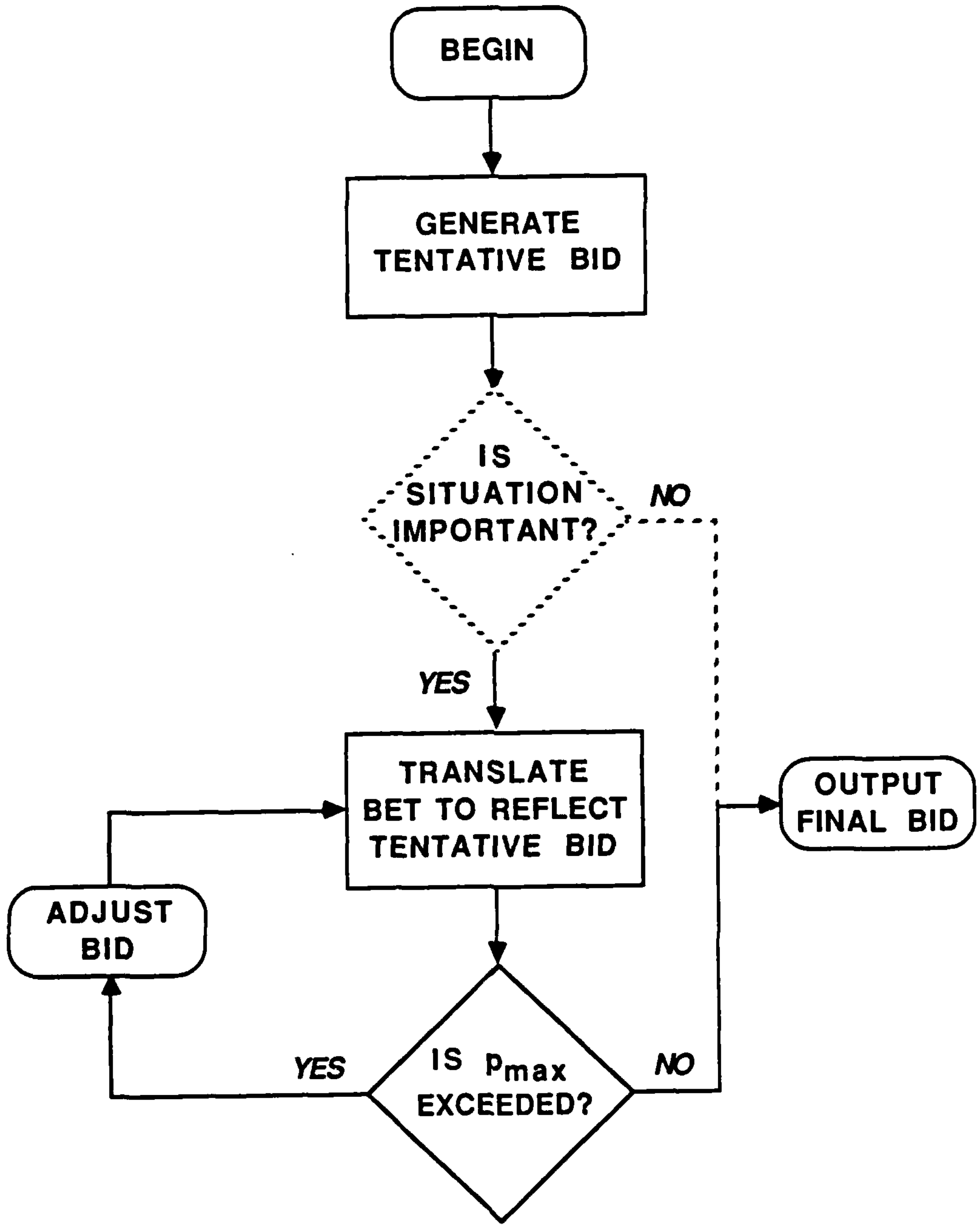


Figure 3

		BID	
		P BET	$ BET
CHOICE	P BET	A NO REVERSAL (SATISFICING)	B *P CHOICE REVERSAL* ANCHORING & ADJUSTMENT
	$ BET	C *$ CHOICE REVERSAL* SATISFICING	D NO REVERSAL (ANCHORING & ADJUSTMENT)

Figure 4


BEGIN
GENERATE TENTATIVE BID
IS SITUATION IMPORTANT?
NO
YES
TRANSLATE BET TO REFLECT TENTATIVE BID
OUTPUT FINAL BID
ADJUST BID
YES
IS p_{max} EXCEEDED?
NO

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